

# Credible Numbers: A Procedure for Reporting Statistical Precision in Parameter Estimates

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-

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# A simple example

## Standard problem:

- Consider an econometrician who want to recover the “impact” of an **explanatory variable  $X_1$**  on an **outcome variable  $y$** , while observing other variables  $X_2$  and  $X_3$ .
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## Usually unknown information:

- The “true” relationship is:

$$y = 1 + 1.234X_1 + X_2 + X_3 + \epsilon$$

where  $\epsilon$  is a non-modelled error term.

- This sample has been generated by taking i.i.d. draws from the following distributions:

$$X_{1t} \sim \mathcal{N}(0, 1), X_{2t} \sim \mathcal{N}(0, 5), X_{3t} \sim \mathcal{N}(0, 10), \text{ and } \epsilon_t \sim \mathcal{N}(0, 5).$$

# Current practice

- The econometrician specifies a handful of models:

**Model 1:**  $y_t = \beta_0 + \beta_1 X_{1t} + \eta_{1t}$

**Model 2:**  $y_t = \beta_0 + \beta_1 X_{1t} + \beta_2 X_{2t} + \eta_{2t}$

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- Results table for **two different sample sizes**:

	Model 1	Model 2	Model 3
$X_1$	1.174** (0.510)	1.176** (0.468)	1.104*** (0.250)
$X_2$		0.864*** (0.196)	0.945*** (0.105)
$X_3$			1.074*** (0.069)
Constant	1.131** (0.459)	1.204*** (0.422)	1.118*** (0.225)
Observations	100	100	100
R <sup>2</sup>	0.051	0.209	0.777

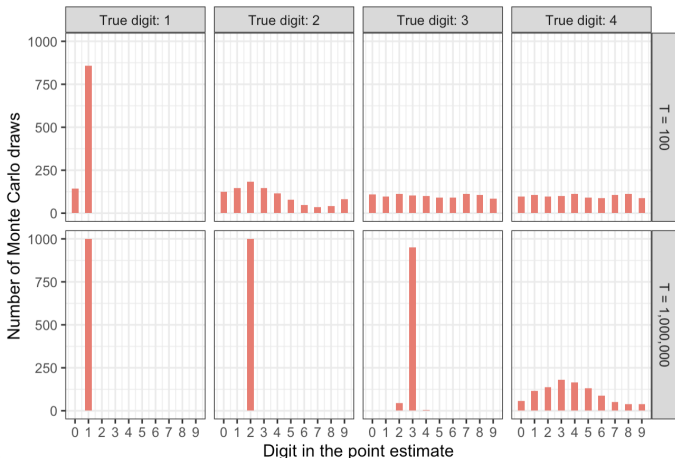
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	Model 1	Model 2	Model 3
$X_1$	1.237*** (0.004)	1.235*** (0.004)	1.234*** (0.002)
$X_2$		0.999*** (0.002)	1.000*** (0.001)
$X_3$			1.000*** (0.001)
Constant	0.999*** (0.004)	0.999*** (0.004)	1.000*** (0.002)
Observations	1,000,000	1,000,000	1,000,000
R <sup>2</sup>	0.071	0.303	0.768

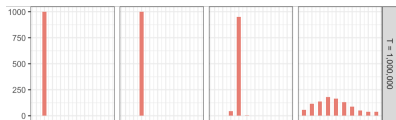
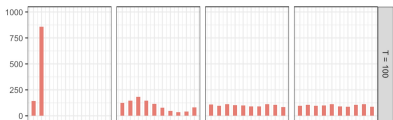
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# Actual precision - Monte Carlo simulation

Distributions of the digits of the coefficient  $\hat{\beta}_1$  across 1,000 draws of datasets (Model 3).



# A different approach?



	Model 1	Model 2	Model 3
$X_1$	1.2 (0.51)	1.2 (0.47)	1.1 (0.25)
$X_2$		0.9 (0.20)	0.9 (0.10)
$X_3$			1.07 (0.069)
Constant	1.1 (0.46)	1.2 (0.42)	1.1 (0.23)
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- 3 Does current practice significantly depart from this reporting rule?  
⇒ Yes: about 60% of the digits printed in the AER between 2000 and 2022 are not significant.

# Outline

- 1 Some econometrics even I understand
- 2 Proposed reporting rule
- 3 Practical significance
- 4 Conclusion

# Framework

- Let  $\hat{\theta}$  be a scalar estimated from observed data by a researcher (e.g. a coefficient estimate).
- Being a finite real number,  $\hat{\theta}$  can be decomposed as a series of digits  $\{\hat{d}_i\}_{i=-\infty \dots D}$ :

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- **Current practice:** pick a default value for  $i_0$ , usually  $-3$ .
- **Our proposal:** choose  $i_0$  endogenously to somehow reflect the level of precision of the estimate.

# Significant digits - Concept

- We propose to build on the literature on “equivalence testing” (Wellek, 2010).
- The objective of an equivalence test is to compare the following hypotheses:

$$H: \theta \leq a \text{ or } \theta \geq b \quad \text{versus} \quad K: \theta \in ]a, b[$$

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- To assess whether digit  $i = 0$  is significant, we test:

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- To assess whether digit  $i = -1$  is significant, we test:

$$H^{i=-1}: |\theta - 1.234| > 0.1 \quad \text{versus} \quad K^{i=-1}: \theta \in ]1.134, 1.334[$$

# Last significant digit

## Definition (Last significant digit)

We define the **rank  $i^*(\alpha)$**  of the “last significant digit” as the smallest value of  $i$  such that digit  $\hat{d}_i$  is significant at level  $\alpha$ :

$$i^*(\alpha) \equiv \min_i \{i \mid \hat{d}_i \text{ is a significant digit at level } \alpha\}$$

Number of sizable digits

# Equivalence testing

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- We propose to adopt the widely used “two one-sided test” (TOST).
- This test rejects the null hypothesis  $H_0^i$  at the level  $\alpha$  if, and only if, the two following standard one-sided tests reject their null hypothesis at the level  $\alpha$ :

$$\begin{array}{lll} H_a^i: \theta = \hat{\theta} - 10^i & \text{versus} & K_a^i: \theta > \hat{\theta} - 10^i (\psi_{ia}) \\ & \text{and} & \\ H_b^i: \theta = \hat{\theta} + 10^i & \text{versus} & K_b^i: \theta < \hat{\theta} + 10^i (\psi_{ib}) \end{array}$$

# Application to standard OLS - Coefficient estimates

- Consider the **standard normal linear conditional mean model**:

$$y = X\beta + \epsilon \quad (1)$$

where the conditional distribution of  $\epsilon$  given the matrix  $X$  is a multivariate normal  $T \times 1$  vector with mean zero and covariance matrix  $\sigma^2 I_T$ .

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- The level  $\alpha$  rank of the last significant digit for  $b_k$  is:

$$i^*(\alpha) = \left\lceil \frac{\ln(SE(b_k)) + \ln(t_{1-\alpha}(T-K))}{\ln(10)} \right\rceil \quad (2)$$

where  $\lceil x \rceil$  denotes the ceiling of  $x$ .

- More generally, a widely applicable asymptotic approximation for the size  $\alpha$  rank of the last significant digit is:

$$i_{\infty}^*(\alpha) = \left\lceil \frac{\ln(SE(b_k)) + \ln(Z_{1-\alpha})}{\ln(10)} \right\rceil \quad (3)$$

where  $Z_{1-\alpha}$ , the  $1 - \alpha$  percentile of a  $\mathcal{N}(0, 1)$  random variable.

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- We assume the researcher observes a sample of  $T = 60$  observations of  $(y_t, X_{1t}, X_{2t}, X_{3t})$  (where  $t$  indexes observations) that has been generated by taking i.i.d. draws from the following distributions:

$$X_{1t} \sim \mathcal{N}(0, 1), X_{2t} \sim \mathcal{N}(0, 5), X_{3t} \sim \mathcal{N}(0, 10), \text{ and } \epsilon_t \sim \mathcal{N}(0, 5).$$

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- We assume the researcher estimates and reports three models:

**Model 1:**  $y = \beta_0 + \beta_1 X_1 + \epsilon$

**Model 2:**  $y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \epsilon$

**Model 3:**  $y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \epsilon$

# Estimation results

Current approach to  
report estimation  
results:

	OLS results		
	Model 1	Model 2	Model 3
$X_1$	0.923 (0.678)	1.018 (0.623)	0.947 (0.366)
$X_2$		0.899 (0.260)	1.005 (0.153)
$X_3$			1.010 (0.097)
Constant	0.945 (0.579)	0.710 (0.536)	0.840 (0.315)
Observations	60	60	60
$R^2$	0.031	0.198	0.728



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	Model 1	Model 2	Model 3
$X_1$	0 (0.6)	1 (0.6)	+0 (0.3)
$X_2$		+0 (0.2)	1 (0.1)
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	Model 1	Model 2	Model 3
$X_1$	0.9 (0.68)	1.0 (0.62)	0.9 (0.37)
$X_2$		0.9 (0.26)	1.0 (0.15)
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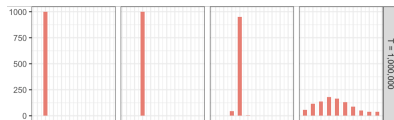
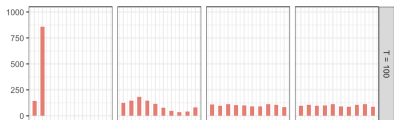
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Removing non-significant digits:

- generally simplifies the presentation of results tables.
- attracts more attention to the magnitude of the estimates.
- makes statistical precision a salient attribute of estimates.

# Which digits are significant?



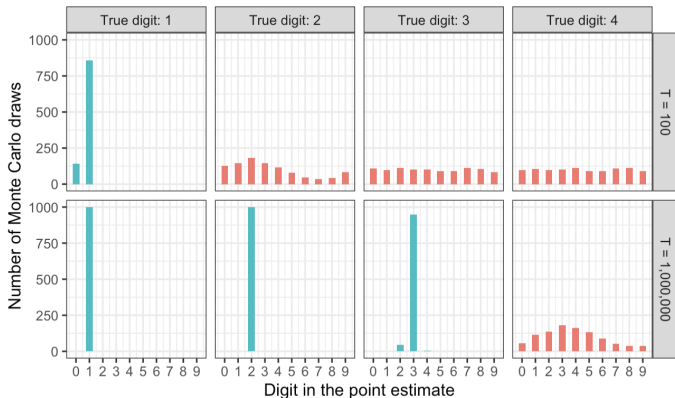
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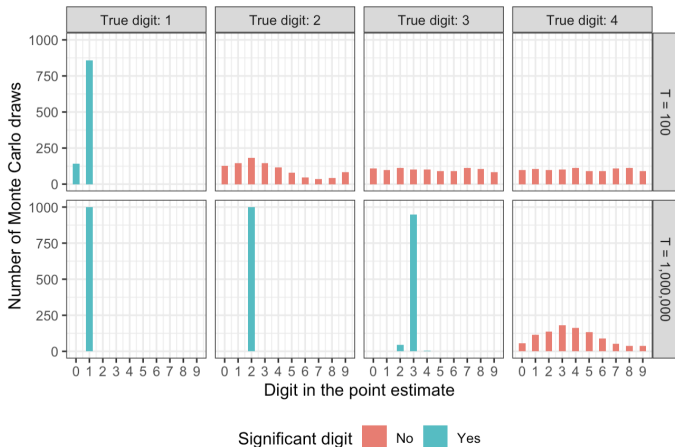
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# Which digits are significant?



Significant digit ■ No ■ Yes

# Which digits are significant?



⇒ We propose that researchers should consider reporting digits only up to the first non-significant one.

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# Data collection

- We retrieve all estimated coefficients and their associated standard error from articles published in the American Economic Review between 2000 and 2022.



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- We obtain a dataset of over 90,000 pairs (coefficient, standard error), as reported in the published articles.
- We focus on coefficient estimates, for which a lower bound of the last significant digit can be built from the sole knowledge of the estimated standard error (asymptotic bound).

# Number of reported decimal digits

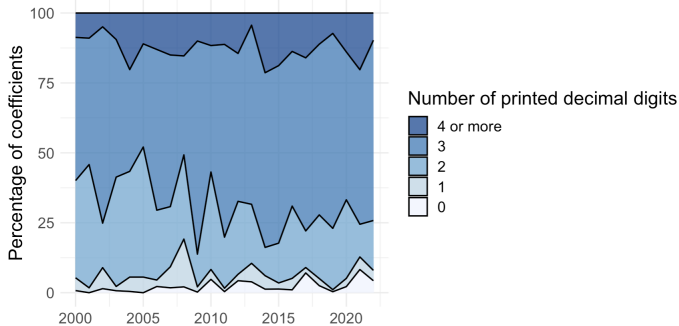
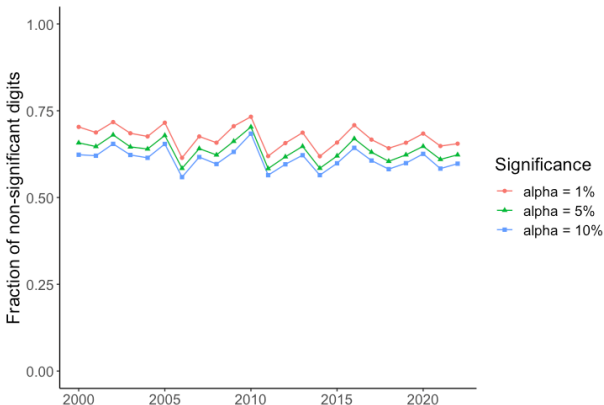


Figure: Number of decimal digits displayed for estimated coefficients.

Coefficients

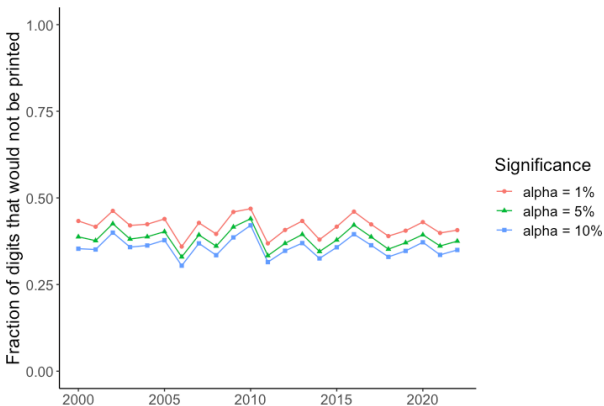
Standard errors

# Main result (1/2)



**Figure:** Fraction of the printed digits of estimated coefficients that are not significant digits at different levels of statistical significance.

# Main result (2/2)



**Figure:** Fraction of the printed digits of estimated coefficients that are not significant digits at different levels of statistical significance.

# Wrapping up

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⇒ We introduce a statistical concept of “significant digits” and propose to report estimates up to the first non-significant digit.
- 2 Would such a reporting rule be easy to implement?  
⇒ Yes. It is for example embedded into the R package `modelsummary`.
- 3 Does current practice significantly depart from this reporting rule?  
⇒ Yes: about 60% of the digits printed in the AER between 2000 and 2022 are not significant.

# Thank you!

[nicolas.astier@psemail.eu](mailto:nicolas.astier@psemail.eu)

## Scientific notations

- The rank of the last significant digit may be a positive power of ten (e.g.  $i^*(\alpha) = 2$ ).
- In such cases, the use of scientific notations would be warranted to avoid reporting non-significant zeros.
- Example: divide the units of  $X_1$ ,  $X_2$  and  $X_3$  by 1,000

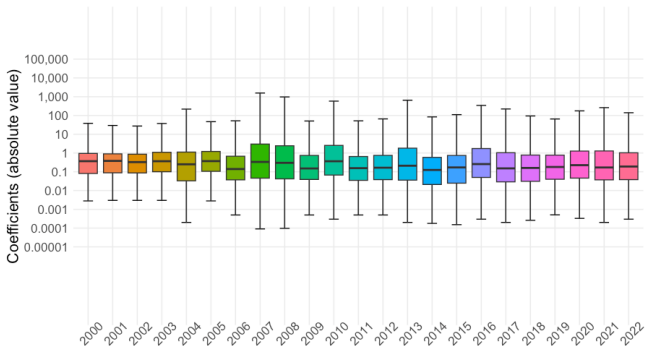
	OLS results		
	Model 1	Model 2	Model 3
$X_1$	9e+02 (6.8e+02)	1.0e+03 (6.2e+02)	9e+02 (3.7e+02)
$X_2$		9e+02 (2.6e+02)	1.0e+03 (1.5e+02)
$X_3$			1.0e+03 (1e+02)
Constant	0.9 (0.58)	0.7 (0.54)	0.8 (0.32)
Observations	60	60	60
R <sup>2</sup>	0.031	0.198	0.728

- Only occurs in a minority of cases in practice.

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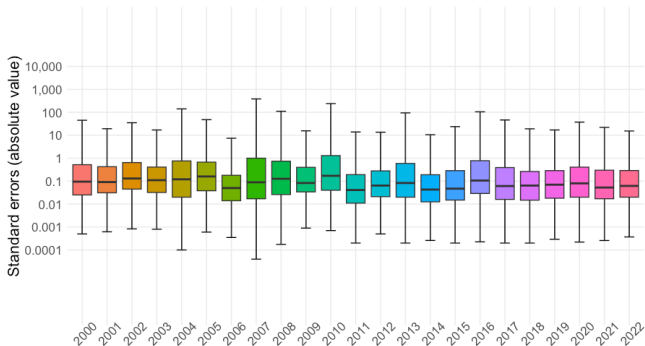


# Distribution of coefficients



**Figure:** Box plots of the magnitude of estimated coefficients (absolute value in  $\log_{10}$  scale). Boxes locate the first, second and third quartiles of the distributions. Top whiskers (resp. bottom whiskers) are drawn at a distance of 1.5 times the interquartile range above the third quartile (resp. below the first quartile).

# Distribution of standard errors



**Figure:** Box plots of the magnitude of estimated standard errors (absolute value in log<sub>10</sub> scale). Boxes locate the first, second and third quartiles of the distributions. Top whiskers (resp. bottom whiskers) are drawn at a distance of 1.5 times the interquartile range above the third quartile (resp. below the first quartile).

## Robustness checks - Main concerns

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- 1 The AER may not be representative of other econ outlets.
- 2 Main coefficient estimates may be more precisely estimated than the coefficients on control variables.

## Robustness checks - Approach

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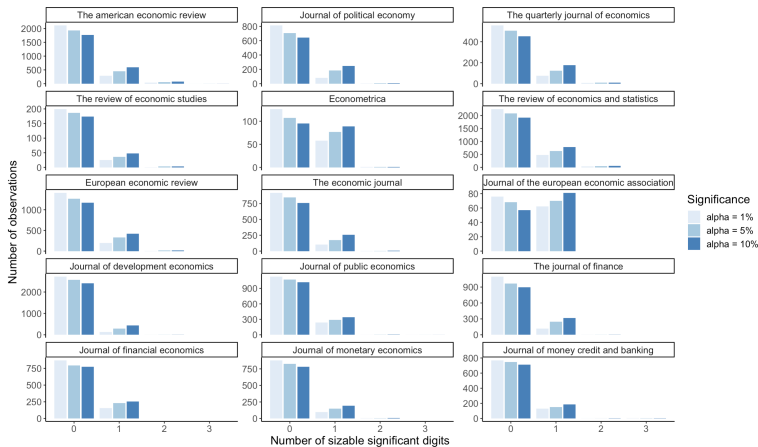
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- We make use of the public dataset by Askarov et al. (JEEA, 2023).
- The authors retrieved the estimated **main effect** and corresponding standard error from over 300 meta-analysis studies.
- We restrict the sample to general interest and field journals in economics.
- The resulting dataset consists of 18,000+ pairs of coefficient and their associated standard error estimates



# Robustness checks - Results



**Figure:** Histograms of the number of sizable significant digits for the different journals.

## Number of sizable significant digits

- The rank of the last significant digit may not be sufficient to capture all the possible interpretations of the concept of “precision”.

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### Definition (Number of sizable significant digits)

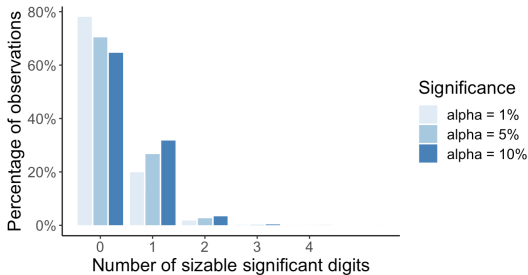
Let  $\hat{\theta} \equiv \sum_{i=-\infty}^{\infty} \hat{d}_i 10^i$  be an estimate of the scalar population parameter  $\theta$ . Let  $D(\hat{\theta})$  equal the largest rank of its non-zero digits:

$$D(\hat{\theta}) \equiv \max_i i \mathbf{1} [\hat{d}_i \neq 0] \quad (4)$$

Let  $i^*(\alpha)$  equal the rank of the last significant digit of  $\hat{\theta}$ . We define the “number of sizable significant digits”,  $\nu(\alpha)$  as:

$$\nu(\alpha) \equiv \max(D(\hat{\theta}) - i^*(\alpha) + 1, 0)$$

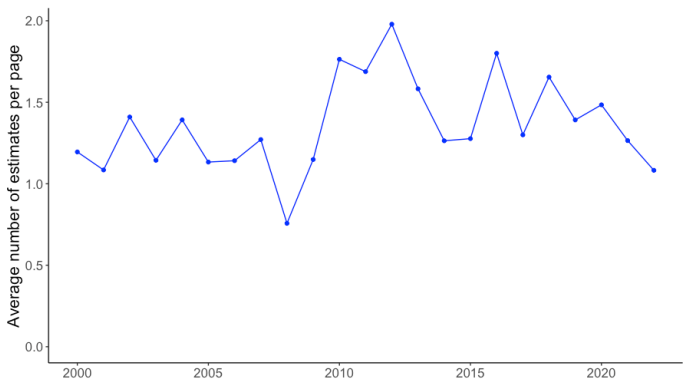
## Main result - Other



**Figure:** Distribution of the number of sizable significant digits.

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# Prevalence of empirical work



**Figure:** Evolution of the ratio of the number of reported empirical estimates in each year over the number of printed pages for that year.